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Target Tracking in Multipath Environments — An Algorithm Inspired by Data Association

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Abstract – *Many wireless sensor networks (WSN) use time of arrival (TOA) based ranging to localize and track the nodes in the network. In non-multipath environments the channel impulse response (CIR) will exhibit a single peak, which corresponds to the direct line-of-sight (LoS) path. In multipath environments, however, the CIR will often contain multiple peaks, and it is not known which peak, if any, is due to the direct LoS path. This problem is similar to the data association problem faced by many target tracking systems. Inspired by this observation, a new algorithm is presented in this paper for target tracking in multipath environments. The proposed algorithm is based on the multidimensional assignment formulation for data association. Through simulations the effectiveness of the proposed algorithm is confirmed.*

Keywords: Wireless sensor networks, localization and tracking algorithms, data association, multidimensional assignment.

1 Introduction

Accurate localization and tracking of nodes is an important requirement in many emerging wireless sensor network (WSN) applications [13]. Existing localization technologies such as global positioning system (GPS) [6] are suitable for some WSN applications, however, their accuracy and operating conditions (GPS works well only in outdoors) are insufficient for many other applications. Hence, development of new localization and tracking technologies is required.

At the Commonwealth Scientific and Industrial Research Organization (CSIRO) a wireless sensor network (WSN) platform, the WASP (Wireless Ad Hoc System for Positioning), is currently under development. This platform is being evaluated for use in applications such as assisting emergency first responders, tracking athletes for performance monitoring, and automation in the mining industry.

The WASP platform uses ranging between pairs of nodes for localization and tracking. Received signal strength is the simplest and lowest cost metric for ranging, however, the resulting accuracy is not adequate for high precision tracking [5]. Ranging based on the estimation of the time of arrival (TOA) of the received signal can result in more accurate range estimates. Accurate and robust TOA estimation, especially in severe multipath conditions, however, is a challenging task [10].

TOA estimation systems rely on the channel impulse response (CIR) and estimate the TOA as the first detected peak or by analyzing the slope of the leading edge. Several factors can cause the first peak not to correspond to the direct line-of-sight (LoS) path [10]. In environments where there is a single radio path between the transmitter and the receiver, such as an open field, the CIR will show a single peak that corresponds to the LoS path. In multipath environments, however, due to several closely arriving pulses the CIR will exhibit several peaks and the peak corresponding to the LoS will be shifted or lost. It is also possible that the strength of the direct path will be well below the detection threshold due to complete obstruction of the path (by for example, a metal object), a strong scatterer near the transmitter, or measurement noise.

Several algorithms have been proposed for increasing the TOA estimation accuracy. For example, increasing the system bandwidth (ultra wideband systems) narrows the pulses arriving from different paths and hence, provides better resolution for the identification of the direct path. Increasing the bandwidth, however, does not improve the TOA estimation accuracy in low signal strength conditions. Besides, the bandwidth available to any system is limited by regulatory and hardware restrictions. Super-resolution algorithms [9] improves the accuracy of the TOA estimation without requiring an increase in the system bandwidth. Such algorithms are found to be computationally expensive and do not seem to increase the estimation accuracy when tested with real data [7].

There is no guarantee that the TOA estimation algorithms will correctly identify and report the arrival time corresponding to the direct path. Therefore it is necessary to check whether a measured range corresponds to the direct

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14. ABSTRACT
Many wireless sensor networks (WSN) use time of arrival (TOA) based ranging to localize and track the nodes in the network. In non-multipath environments the channel impulse response (CIR) will exhibit a single peak which corresponds to the direct line-of-sight (LoS) path. In multipath environments, however, the CIR will often contain multiple peaks, and it is not known which peak, if any, is due to the direct LoS path. This problem is similar to the data association problem faced by many target tracking systems. Inspired by this observation, a new algorithm is presented in this paper for target tracking in multipath environments. The proposed algorithm is based on the multidimensional assignment formulation for data association. Through sim- ulations the effectiveness of the proposed algorithm is con- firmed.

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path. Several algorithms proposed to solve this problem consider positioning in cellular networks and assume that ranges due to multipath propagation are positively biased (for example, [19] and references cited therein). Data collected from field trials, however, suggest that the CIR can contain peaks even before the LoS peak. These early peaks can be due to noise, sidelobes of NLoS path signals with higher amplitude than the LoS path signal, or other signal processing artifacts. As a result range measurements in multipath conditions can be negatively biased as well as positively biased. Most of the algorithms presented in the literature do not consider this and hence, may not work well in practice.

In this paper a new algorithm for tracking nodes in multipath environments, which is inspired by the observation that this problem is similar to the well-known data association problem, is proposed. The proposed algorithm is based on the multidimensional assignment (MDA) formulation for data association. This formulation results in an NP-hard problem and hence, it is not possible to obtain the optimal solution using polynomial time complexity algorithms. Lagrangian relaxation-based algorithms are available to obtain suboptimal solutions. As shown later in this paper, however, the algorithm presented for tracking in multipath environments does not result in an NP-hard problem, instead requiring a simple minimization to obtain the optimal solution.

The rest of the paper is organized as follows. In Section 2 a brief description of the WASP platform and the problem considered in this paper are explained. Section 3 explains the MDA formulation for the data association problem. The proposed algorithm for tracking in multipath environments is described in Section 4 and the simulation results are presented in Section 5. Concluding remarks are provided in Section 6.

2 Background

The objective of the WASP platform design is to develop a truly ad-hoc WSN platform that could be used in many different WSN applications as possible with very little customization. This platform operates in the industrial, scientific, and medical (ISM) frequency bands and uses TOA-based ranging. Further, it uses a single radio for ranging and data communication (if required by the application). To reduce the cost, the design uses low-cost commodity hardware and solves problems such as radio bandwidth limitation and lack of time and frequency synchronization that arise due to the use of such hardware using sophisticated signal processing techniques.

One consequence of the design objective is that it needs to be capable of operating both indoors and outdoors. For example, one area in which the WASP platform has been field tested extensively is tracking athletes, where the requirement is that the platform must be capable of providing comparable accuracy in both indoor and outdoor sports. Another application where WASP is field tested is the automation of mining. In this application the system is expected to operate underground and in open areas seamlessly.

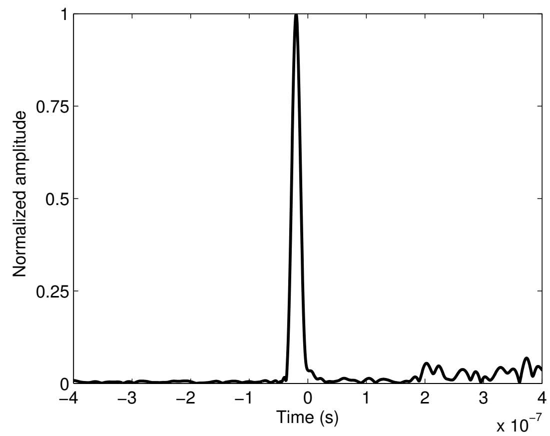

Figure 1: CIR in an outdoor environment showing a clear peak corresponding to the LoS path.

2.1 Problem formulation

The type of WSN considered in this paper consists of a number of anchors whose locations are known, and it is required to track the remaining nodes in the network. It is assumed that there exist direct paths between the anchors and the nodes, and that the anchors send the measured ranges to a central location server where the tracking is performed. Such a setup is adequate, for example, to track the athletes.

Although the applications require multiple nodes to be tracked, the WASP platform does not face the data association problem [2] encountered by most multitarget tracking systems. This is because WASP uses time division multiple access (TDMA) to control the transmission by nodes, meaning that a node is allowed to transmit only at specified time slots. Hence, the multitarget tracking problem reduces to tracking multiple single targets and in the rest of the paper single target tracking is considered. Since the range measurements are synchronized and sent to a central location server for tracking, the resulting system is a Type 3 track initialization and maintenance system [4].

At each time slot in the TDMA frame anchors receive the transmission from the node that transmits in this slot and each anchor constructs the CIR. Figures 1 and 2 show the sample CIR constructed by the WASP in an outdoor and an indoor environment, respectively. The outdoor CIR shows a clear peak corresponding to the LoS path, however, there are several comparable peaks in the indoor CIR. It is not clear which peak, if any, corresponds to the LoS path. Selection of the incorrect peak for TOA estimation could lead to a large range measurement error. In this paper it is assumed that the anchors identify all the peaks (up to the strongest peak, since LoS path cannot occur after this) in the CIR and

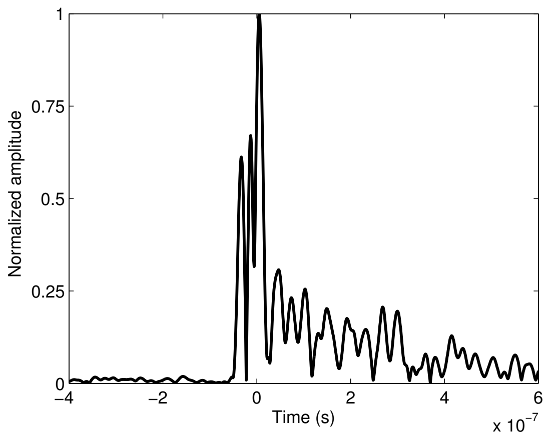

Figure 2: CIR in an indoor environment showing significant multipath condition.

report all the ranges corresponding to these peaks to the central location server, where the identification of the LoS path and the update of the track is performed.

3 Data association

Deciding from which target, if any, a certain measurement originated is one of the most challenging issues in multitarget tracking systems. This is referred to as the data association problem and has been studied extensively since [18]. A number of algorithms have been developed to solve this problem, which differ in the complexity and the resulting tracking performance. Details on the the data association algorithms can be found in [2] and the references cited therein.

A well-known solution for the data association problem is the MDA formulation [3, 15], which is a discrete optimization formulation of the problem. This formulation can also be viewed as an approximation to the optimal multiple hypothesis tracking (MHT) algorithm [16] in which the number of association hypotheses, however, increases exponentially. The MDA formulation in effect uses a sliding window to keep the number of hypotheses manageable.

Consider the data association problem in Type 3 track initialization and maintenance systems. In such systems, at every time step the data association problem is solved in two steps: 1) the measurement-to-measurement or static association and 2) the measurement-to-track or dynamic association. The static association groups the measurements from different sensors[1] that have originated from the same target and the dynamic association assigns the grouped (combined or composite) measurements to the tracks from the previous scan. An assignment-based solution [12] formulates the static and dynamic associations as multidimensional and two dimensional assignments respectively.

[1]Note that the terms anchors (prevalent in sensor network literature) and sensors (prevalent in target tracking literature) are used interchangeably.

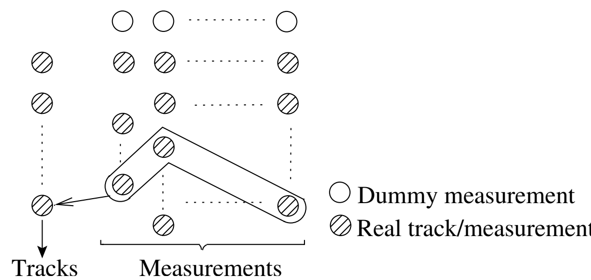

Figure 3: $(S+1)$-D data association.

In [17] an extension to the above two-step MDA formulation for data association in Type 3 systems is presented. This algorithm is still a MDA formulation, however, it solved the data association problem in a single step. This algorithm forms the basis for the proposed tracking algorithm in multipath and is explained next.

3.1 $(S+1)$-D assignment algorithm for data association

Assume that there are S sensors in a Type 3 system. Being synchronous sensors each returns observations at specified time intervals. Let the number of measurements returned by sensor s, $s = 1, 2, \ldots, S$, at scan k be n_s. Also denote by z_{si_s} the individual measurement returned by sensor s. Note that $i_s = 1, 2, \ldots, n_s$. Further, assume that n_T tracks are available from the previous scans. The objective is to identify the measurements from different sensors that originated from the targets corresponding to the tracks.

The $(S+1)$-D scenario is illustrated in Figure 3, where the first dimension is the tracks from the previous scan and the rest of the S dimensions are the lists of measurements from the S sensors. In addition to the measurements returned by each sensor the measurement dimensions have dummy measurement as shown in Figure 3, which accounts for missed detection [12].

In the $(S+1)$-D assignment, an $(S+1)$-tuple consists of a track and S measurements, at most one from each sensor. The cost of an $(S+1)$-tuple $(p, i_1, i_2, \ldots, i_S)$, i.e., the cost of assigning an S-tuple of measurement $(i_1, i_2, \ldots, i_S)$ to the track p, is defined as

$$c_{pi_1 i_2 \cdots i_S} = -\log \frac{p(Z_{i_1 i_2 \cdots i_S} | X_p)}{p(Z_{i_1 i_2 \cdots i_S} | p = \emptyset)} \qquad (1)$$

where X_p is the state of target p and $Z_{i_1 i_2 \cdots i_S} = \{z_{1i_1}, z_{2i_2}, \ldots, z_{Si_S}\}$ is the S-tuple of measurements. The numerator is the likelihood that the S-tuple of measurement originated from the target corresponding to track p, and the denominator is the likelihood that all the measurements in the S-tuple are spurious.

The objective now is to find the most likely set of $(S+1)$-tuples so that each measurement is assigned at most to one track and each track is assigned at most to one measurement from each sensor. This is formulated as a generalized MDA problem given by [12]

$$\min_{\rho_{pi_1i_2\ldots i_S}} \sum_{p=0}^{n_T}\sum_{i_1=0}^{n_1}\cdots\sum_{i_S=0}^{n_S} c_{pi_1i_2\ldots i_S}\rho_{pi_1i_2\ldots i_S} \tag{2}$$

subject to:

$$\begin{aligned}
&\sum_{i_1=0}^{n_1}\sum_{i_2=0}^{n_2}\cdots\sum_{i_S=0}^{n_S}\rho_{pi_1i_2\ldots i_S}=1, \quad p=1,2,\ldots,n_T\\
&\sum_{p=0}^{n_T}\sum_{i_2=0}^{n_2}\cdots\sum_{i_S=0}^{n_S}\rho_{pi_1i_2\ldots i_S}=1, \quad i_1=1,2,\ldots,n_1\\
&\quad\vdots \qquad\qquad \vdots \qquad\qquad \vdots\\
&\sum_{p=0}^{n_T}\sum_{i_1=0}^{n_1}\cdots\sum_{i_{S-1}=0}^{n_{S-1}}\rho_{pi_1i_2\ldots i_S}=1, \quad i_S=1,2,\ldots,n_S
\end{aligned} \tag{3}$$

where $\rho_{pi_1i_2\ldots i_S}$ is a binary variable such that

$$\rho_{pi_1i_2\ldots i_S}=\begin{cases}1 & \text{if } (S+1)\text{-tuple is included in the solution set}\\ 0 & \text{otherwise}\end{cases} \tag{4}$$

The generalized MDA problem above can be shown to be NP-hard for $S \geq 3$ even under the assumptions of unity detection probability and no spurious measurements [11]. As a result, finding the optimal solution is impractical using polynomial time complexity algorithms. Therefore, for applications such as target tracking that require real-time performance, algorithms seeking suboptimal solutions in polynomial time complexity are required. One can find such suboptimal algorithms in [3, 12, 14].

4 Target tracking in multipath

As mentioned before target tracking in multipath conditions is similar to the data association problem described in the previous section.

- Each measurement list consists of the ranges corresponding to the peaks in the CIR.
- There could be at most one LoS range in each measurement list.
- It is possible that an anchor does not have the LoS path to the node, which is accounted for by the dummy measurement.
- Unlike in the data association problem there is only one track in the track list. This is because of the use of TDMA scheduling in WASP.
- The objective is to find the LoS measurements from each list that has originated from the targets corresponding to the tracks in the track list.

It is clear that the above problem is similar to the data association problem and the MDA formulation can be applied to solve it. Note that since there is only one track in the first dimension, only a single $(S+1)$-tuple that minimizes the assignment cost is required to be found. Therefore, the one-to-one correspondence requirement that one measurement can be assigned at most to one track and vice versa is eliminated. Consequently, the need for solving the NP-hard minimization problem defined in (2) and (3) is eliminated and a simple minimization is suffice. That is[2]

$$\min_{i_1,i_2,\ldots,i_s} c_{i_1i_2\ldots i_s} \tag{5}$$

where the cost of an $(S+1)$-tuple is again a likelihood ratio as in (1), which is given by [17]

$$\begin{aligned}c_{i_1i_2\ldots i_s} &= -\log p(r|\hat{X})+\\ &\sum_{s=1}^{S}[u(i_s)-1]\ \ln(1-P_{D_s}) - u(i_s)\ \ln(P_{D_s}\,\psi_s)\end{aligned} \tag{6}$$

In (6), r is the vector [defined in (16)] consisting of at most one range measurement from each anchor, $\hat{X}$ is the predicted state, P_{D_s} is the probability with which the LoS peak appears in the CIR for sensor s, and ψ_s is the density of false peaks. $u(i_s)$ is a binary variable defined by

$$u(i_s)=\begin{cases}0 & \text{if } i_s=0\\ 1 & \text{otherwise}\end{cases} \tag{7}$$

4.1 Initialization

The proposed tracking algorithm assumes that the track has already been initialized. To perform track initialization, the MDA formulation for static association [11] can be used. In this formulation, since there is no track information initially, the track list in Figure 3 is absent and with S anchors one will have S-dimensional assignment problem. The cost of an S-tuple is defined as a likelihood ratio as in (1), however, since track information X_p is not available, following [11], it is replaced by the maximum likelihood (ML) estimate of the S-tuple. That is

$$c_{i_1i_2\cdots i_S} = -\log\frac{p(Z_{i_1i_2\cdots i_S}|X_{ML})}{p(Z_{i_1i_2\cdots i_S}|p=\emptyset)} \tag{8}$$

where

$$X_{ML}=\arg\max_{X}\ p(Z_{i_1i_2\cdots i_S}|X) \tag{9}$$

Hence, once all possible costs defined in (8) are found, since the single best hypothesis is required (because a single target being initialized), the S-tuple with the minimum cost is selected and used to initialize the track. A flow chart of the proposed algorithm is shown in Figure 4.

[2]Since there is only one track the track index is omitted.

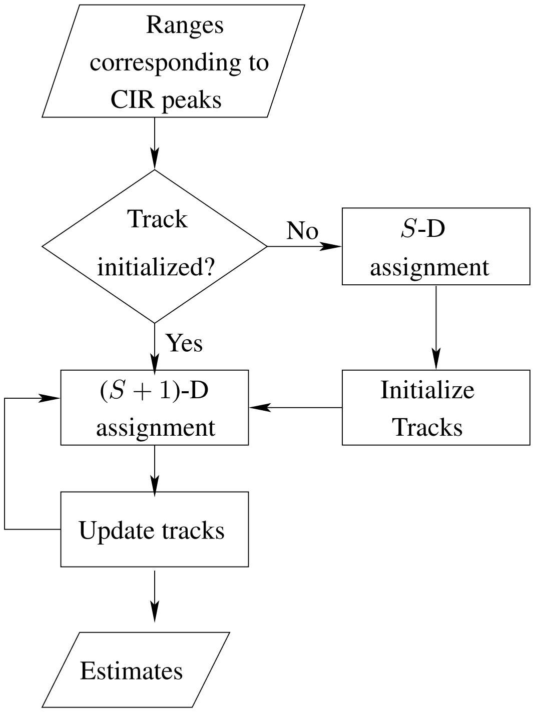

Figure 4: Flow chart of the proposed tracking algorithm in multipath conditions.

5 Simulations

The performance of the proposed algorithm is evaluated using simulations. Single target tracking is assumed since as explained before the WASP platform does not encounter the data association problem. The scenario considers tracking a cyclist in a velodrome as shown in Figure 5. The anchor layout was from one of the field trials carried out in Adelaide, Australia. The velodrome track and anchor locations were obtained through a field survey.

5.1 Scenario

The target is constrained to move within the velodrome track and the true trajectories are generated using nearly constant velocity (NCV) and coordinated turn (CT) models [1]. The NCV model is defined by

$$X_k = F_k^{CV} X_{k-1} + v_{k-1} \tag{10}$$

where $X_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T$ is the state of the target at time t_k, F_k^{CV} is the state transition matrix, and v_{k-1} is the zero mean Gaussian process noise with covariance Q_k. F_k^{CV} and Q_k are given by

$$F_k^{CV} = I_2 \otimes \begin{bmatrix} 1 & T_k \\ 0 & 1 \end{bmatrix} \tag{11}$$

$$Q_k = I_2 \otimes \begin{bmatrix} T_k^3/2 & T_k^2/2 \\ T_k^2/2 & T_k \end{bmatrix} \tilde{q} \tag{12}$$

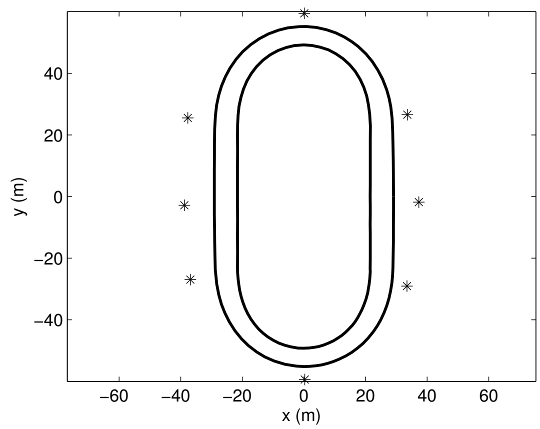

Figure 5: Simulation scenario. The velodrome track and nine anchors (shown as *). The target trajectory was constrained within the velodrome tracks.

where $T_k = t_k - t_{k-1}$, $\tilde{q}$ is the process noise intensity, and I_2 is a 2×2 identity matrix, and $\otimes$ denotes the Kronecker product. The CT model is defined by

$$X_k = F_k^{CT} X_{k-1} + \Gamma_k v_{k-1} \tag{13}$$

where

$$F_k^{CT} = \begin{bmatrix} 1 & \frac{\sin \Omega_k T_k}{\Omega_k} & 0 & -\frac{1-\cos \Omega_k T_k}{\Omega_k} & 0 \\ 0 & \cos \Omega_k T_k & 0 & -\sin \Omega_k T & 0 \\ 0 & \frac{1-\cos \Omega_k T_k}{\Omega_k} & 1 & \frac{\sin \Omega_k T_k}{\Omega_k} & 0 \\ 0 & \sin \Omega_k T_k & 0 & \cos \Omega_k T & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{14}$$

$$\Gamma_k = \begin{bmatrix} 0.5T_k^2 & 0 & 0 \\ T_k & 0 & 0 \\ 0 & 0.5T_k^2 & 0 \\ 0 & T_k & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{15}$$

Note that while generating the CT segment of the trajectory the state is augmented with the turn rate. It is, however, not tracked.

The LoS measurements identified using the proposed algorithm are collected in to a measurement vector. The measurement model is then

$$r_k = h(X_k) + w_k \tag{16}$$

where with S anchors reporting LoS ranges the measurement function $h(.)$ is given by

$$h(X_k) = \begin{bmatrix} \| HX_k - \theta_1 \| \\ \| HX_k - \theta_2 \| \\ \vdots \\ \| HX_k - \theta_S \| \end{bmatrix} \tag{17}$$

where $\theta_i = [x_i, y_i]^T$ is the known location of sensor i, $i = 1, 2, \ldots, S$ and

$$H = I_2 \otimes \left[\begin{array}{cc} 1 & 0 \end{array} \right] \tag{18}$$

Measurement noise in each anchor is assumed to be Gaussian distributed with zero mean and variance σ_s^2, $s = 1, 2, \ldots, S$, and uncorrelated between the anchors. Consequently, w_k is zero mean Gaussian vector with covariance $R = \mathrm{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_S^2)$.

At each time scan the LoS measurement for sensor s is generated with probability P_{D_s} and the number of non LoS (NLoS) measurements for sensor s is assumed to be Poisson distributed with rate λ_s. It is assumed that the NLoS measurements are uniformly distributed in $[r_{los,s} - r_{b,s}, r_{los,s} + r_{a,s}]$, where $r_{los,s}$ LoS range between the target and sensor s. Although these assumptions (i.e., Poisson distribution for the number and uniform distribution for the spatial density of false alarms) are not strictly true for NLoS measurements, it is still used for simplicity.

The interacting multiple model (IMM) estimator [1] consisting of two filter modules, is used to track the node. The measurement model is the same for both filters (16), and both filters used the NCV model for target dynamics, however, with different noise intensity levels. Although the process model is linear, the measurement model described above is nonlinear, and hence a nonlinear filter is required. The unscented Kalman filter (UKF) [8] is chosen as the constituent filter in the IMM estimator.

The proposed algorithm is compared against an algorithm that assumes the first peak in the CIR as the TOA. For tracking the node the latter algorithm used the same IMM framework as the proposed algorithm. The smallest range that each anchor reported is used to update the track.

5.2 Results

In this particular simulation the following parameters are used for all sensors: $P_{D_s} = 0.9$, $\lambda_s = 3$, $r_{b,1} = 6$m, $r_{a,2} = 8$m, and $\sigma_s = 0.3$m. The sampling period is assumed to be 1s. The noise intensity level of the two NCV models used in the tracker is 0.5 and 5m^2/s^3, respectively. The following mode transition probability matrix is used in the IMM estimator.

$$\left[\begin{array}{cc} 0.90 & 0.10 \\ 0.15 & 0.85 \end{array} \right] \tag{19}$$

The estimation performance of the proposed and first peak algorithms along with the ground truth for a sample run is shown in Figure 6. It is clearly evident that the procedure to identify the LoS peak improves the tracking performance.

In 100 Monte Carlo runs the proposed algorithm identified the LoS peak with 83.3% success rate. Note that if the LoS was not detected at an anchor and the proposed algorithm assigned the track to the dummy measurement of that anchor it was also considered a successful identification.

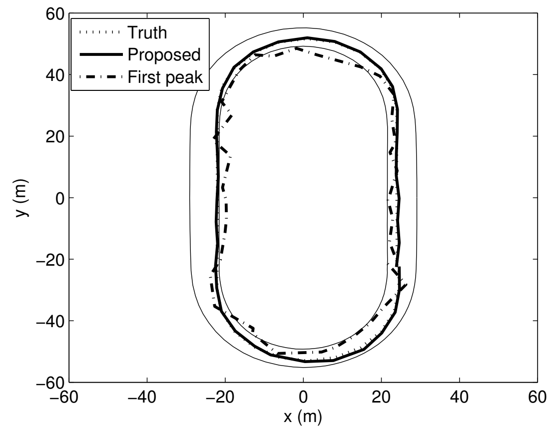

Figure 6: Estimation performance of the proposed and first peak algorithms on a sample run.

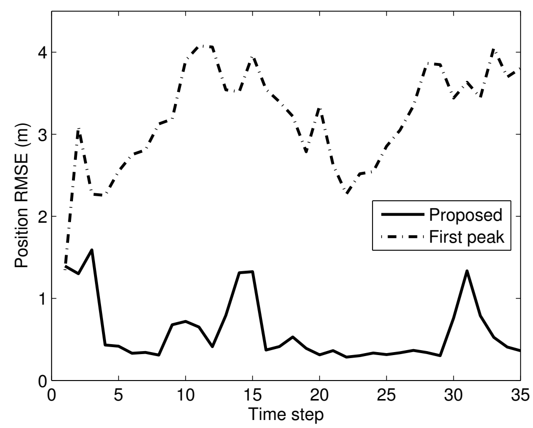

Figure 7: Position RMSE for the proposed method and the one that selects first peak as the LoS range.

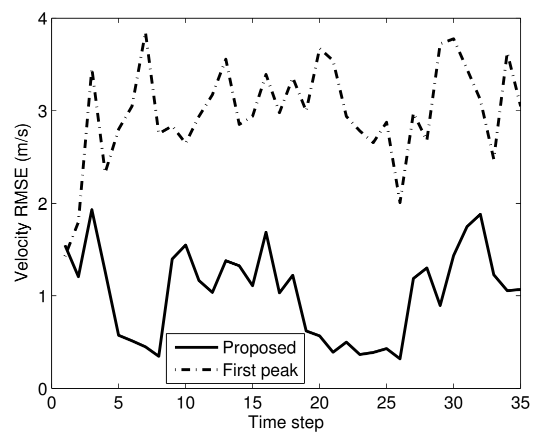

Figure 8: Velocity RMSE for the proposed method and the one that selects first peak as the LoS range.

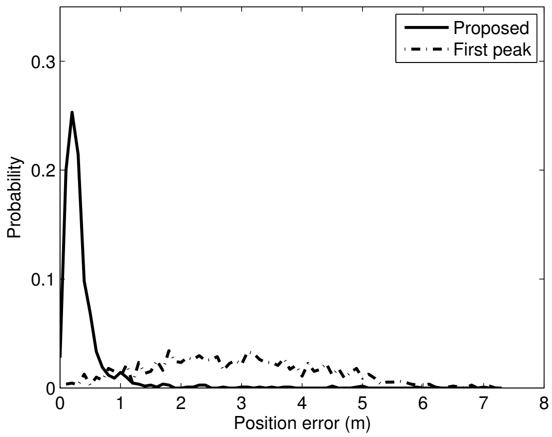

Figure 9: Positioning error pdf for the proposed and first peak algorithms.

The position and velocity root mean squared error (RMSE) performance of the two algorithms is shown in Figures 7 and 8 respectively. As seen from the figure, the position and velocity RMSE are nearly halved by the proposed algorithm.

The error probability density function is shown in Figure 9, which provides some insight about the spread of the positioning error. It can be easily seen that most of the probability mass of the positioning error is less than 1m for the proposed algorithm, which is not the case for the first peak algorithm. In fact for the proposed algorithm the probability mass inside the 1m error is 0.94, while that for the first peak algorithm is just 0.08. The maximum positioning error observed for both the algorithms is similar: 6.96m for the proposed algorithm and 7.32m for the first peak algorithm.

6 Conclusions

In this paper an algorithm for target tracking in the multipath conditions was presented. The algorithm was inspired by the observation that the problem at hand is similar to the multitarget data association problem. In particular, the proposed algorithm used the MDA formulation for data association in Type 3 track initialization and maintenance systems, however, as shown in the paper it did not result in an NP-hard problem. The solution was a simple unconstrained minimization.

The proposed algorithm was evaluated using simulations and gave a positioning error of less than 1m with a probability of 0.94. Corresponding figure for an algorithm that assumes the first peak in the CIR as the LoS measurement was 0.08. Currently work is in progress to compare the proposed algorithm with other NLoS mitigation algorithms and also to test it using data collected in real multipath environments using the WASP platform.

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